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OPTIMIZATION OF DIMENSIONAL, SURFACE QUALITY AND MATERIAL REMOVAL RATE IN TURNING USING RESPONSE SURFACE METHODOLOGY AND DUELIST ALGORITHM

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ABSTRACT

Measuring the productivity and surface quality of turning process, mainly depends on performance parameters, like surface roughness, roundness error and rate of material removal. The main goal of this paper is to investigate the cut depth effect, cutting speed and turning process feed rate for AISI4145 alloy steel performance parameters. Experimentaly designed RSM (Response Surface Methodology) implmented to correlate between the cutting condition parameters and its turning process performance. The efficiency of the proposed models was tested through analysis of variance (ANOVA). A novel optimization technique, known as Duelist Algorithm is then applied for finding the optimal combination between the cutting process parameters and its effect on the process performance parameters. It is done by minimizing the values of both surface roughness and roundness error alongside maximizing the material removal rate. The optimal solutions were confirmed experimentally.

KEYWORDS: RSM, ANOVA, DA, Roughness & Roundness

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Original Article

1. INTRODUCTION

Alloy Steel 4145 has a wide applications area at oil and gas industries, like pup joints, subs and drill collars. forged gears and shafts for hydraulic presses. Thus, the optimaization of the factors that have an effect on the surface quality and the productivity of 4145 steel alloy is inportant.

Optimizing the cutting processes, no matter what their type, is an important issue, as it affects the whole manufacturing process from different aspects. Turning process is one of the most important metal cutting operations utilized in producing round and cylindrical steel components.

The quality of the surface finish, dimensional tolerance and material removal rates are the three important factors that must be controlled in the turning process. The cutting process parameters (conditions) contain current speed, feed rate and depth of cut; using coolants will exert an impact on machining and surface quality conditions, which are material removal rates and surface roughness, respectively.

Roundness error of circular components and dimensional deviations of the product also affect the cutting process papameters. Kalpakjian *et al*., 2001. M. Rahman *et al*., 1986, optimized roundness error for achieveing the maximum possible material removal rate accurately.

Yang *et al*., 1998, applied Taguchi approach to investigate the machining performance of high carbon S45C steel bars employing tungsten carbide tools. Also, optimization of cut depth values, cutting speed and feed rate in turning process and its effect on performance parameters, such as surface roughness and tool life were considered.

Influnce of cut depth, cutting speed and feed rate with the cutting time on metal matrix composites' turning was investigated by Davim *et al*., 2003.

Correlating surface coditions in terms of surface roughness (R_a) and removal rate (R_t) at different turning machining conditions for Aluminum–Silicon metal matrix composites, the multiple-linear mathematical models is used, Manna *et al*., 2004. Aslan *et al*., 2007 optimized cutting conditions of turning process for AISI 4140 steel with using aluminum oxide and titanium carbon nitride mixed with ceramic tool and analysis of variance ANOVA process that achieves something better defined as optimization process, M. Chandrasekaran *et al*., 2010. It involved three sections, which are model, objective function and optimization algorithm sections model.

Rangwala Dornfeld *et al.* 1989, predicting cutting performance during turning process done by an applied set of input patterns throught feedforward neural network. Natarajan *et al*., 2006 used particle swarm optimization for optimizing neural network prediction of tool life, to reduced training time by 50%.

Li *et al*. 2000, employed neuro-fuzzy techniques to estimate the feed forced by measuring motor current by sensor in computer numerical control centire lathe machine.

Palanisamy *et al*., 2007, applied genetic algorithm technique to optimize cutting conditions of milling machining and minimize machining time.

Saravanan *et al*., 2007, minimized machining time done through optimal cutting speed and feed rate for turning process by using genetic algorithm.

R. V. Rao *et al.*, 2009, used artificial bee colony to improve process conditions (cutting speed and surface roughness) of the electrical discharge machining.

Zheng *et al*., 2010 used particle swarm optimization for optimizing multi-pass turning process conditions and minimizing unit production cost.

The cuckoo search algorithm used by Ali, R. Yildiz *et al.*, 2013 to improve machining conditions for milling process, compared between the results of using that algorithm and other evolutionary algorithms (particle swarm and genetic algorithm) appeared optimization of machining conditions.

Girish Kant *et al*., 2015, optimizining machining process conditions (4.65 m/sec cutting speed, 0.142 mm/tooth feed rate and 0.67 mm depth of cut) and minimize surface roughness (0.099 μm) done based on neural network.

The response surface methodology and genetic algorithm were used by Kuldip S. Sangwan *et al*., 2017, for predicting the energy consumption along with the corresponding cutting parameters on turning process of AISI 1045 steel.

A novel algorithm called Jaya algorithm was applied by Rao *et al*., 2017 to optimize machining conditions for electrical discharge and electrochemical machining. The results showed a good performance for Jaya algorithm in comparison with other algorithms.

Ingenetic algorithms in Tanveer *et al*., 2013, two ways used for developing, one individual to produce a new offspring and the other is an individual mutate into new duelist algorithm. DA (duelist algorithm) defined as the individual in population.

Totok R. Biyanto, *et al*., 2017, used duelists fight to determine the losers, winners and champions. DA tries to minimize the blind effect based on their classification.

In the present paper, duelist algorithm based on genetic algorithm is applied on AISI alloy steel 4145 due to its wide usage in industry. The optimization parameters are surface roughness, roundness error, and material removal, which appears at surface quality, dimensional quality and productivity measurement values. The study will also provide a reliable investigation on optimizing the machining process for AISI steel in industry, based only on the available required cutting ranges of the available machine tools. Moreover, it provides a full preview on employing such algorithm in different manufacturing optimization problems.

2. MATERIAL AND METHODOLGY

In the workpiece that is used in this experiment made of round bars from AISI 4145 alloy steel with diameter 25 mm and 80 mm length, as shown in figure 1.

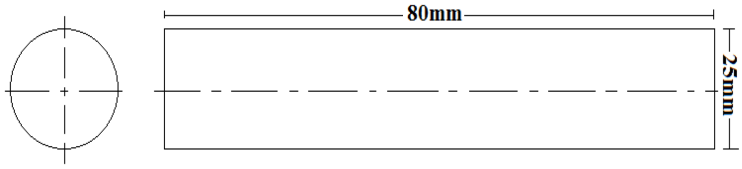

Figure 1: AISI 4145 Alloy Steel Bar.

The chemical composition and mechanical properties of AISI 4145 alloy steel explained in tables 1 and 2, respectively. A conventional center lathe with center distance of 1.5 meter, spindle speed range is (45– 2445 r.p.m), and feed range is (0.08 - 0.38 mm/rev.).

Table 1: Chemical Composition of Steel 4145

Element	C	Mn	Cr	Mo	Si
%	0.44	0.89	0.88	0.23	0.2

Table 2: Mechanical Properties of Steel 4145

Properties	Elastic Modulus (GPa)	Hardness (Brinell)	Shear Modulus (GPa)	Bulk Modulus (GPa)
Values	200	308	80	140

The tool used in this work was made of cemented carbide material inserts with specfication, as shown in table 3.

Table 3: Specfication of Cemented Carbide Tool

Rake Angle α (°)	Cutting Edge Angle β (°)	Clearance Angle γ (°)	Nose Radius r (mm)
5	80	7	0.4

The surface roughness parameter (R_a) of the workpiece after machining was measured with Surftest SJ-310 instrument, while the roundness testerTalyrond 73 - Taylor Hobson, S/no. 112/2802-0123, L.R. = 0.01 µm.

2.1 Uncertainty (U)

Uncertainty evaluation dtermined in accordance with the JCGM 100:2008.

$U = \pm 2.0\ \mu m$

U = uncertainty expanded using coverage factor K = 2, level confidence approximately 95%.

2.2 Traceability

All equipments used for measurement are traceable to gauge blocks, which were calibrated by optical interferometer at KRISS traceable to SI units, certificate No: 05-03031-001.

2.3 Environmental Conditions: $20^0C \pm 1^0\ C$

Used for measuring roundness error.

2.4 Experimental Design using RSM

The experimental design is performed for realizing the effect of different parameter levels and a response as well as the interactions of the several factors. The experimental design for investigating effect of different turning process conditions (depth of cut, cutting speed and feed rate) on the machining characteristics (surface roughness, roundness error and the material removal rate), was done. In this paper, the experiments were designed using response surface method, employing central composite-second-order rotatable consisting of 2k factorial, where k represents the number of variables, the number of experiments (N) can be found from the following equations:

$$N = n_c + n_a + n\ldots, \tag{1}$$

$$n_c = 2k\ldots, \tag{2}$$

$$n_a = 2k\ldots, \tag{3}$$

where

n_c = number of corner points.

n_a = number of axial points of the unit cube that constitutes of a central composite design.

Factors and factor levels summarized in table 4.

Table 4: The Factors and Factor Levels

Cutting Speed (m/min)	Feed Rate (mm/rev.)	Depth of Cut (mm)
80	0.08	0.3
115	0.16	0.6
150	0.23	0.9

2.5 Methodology of Response Surface

In that research, methodology of response surface used to determine the relation between turning process conditions (depth of cut, cutting speed and feed rate) and different machining criteria. Also, study the effect of turning process conditions on performance parameters (surface roughness, roundness error and the material removal rate). To do that, a response surface second-order polynomial mathematical models were developed, and a designed expert computer software was used for

solving these polynomial mathematical equations to study the performance of affected parameters with change in cutting parameters values, as following sections describe.

2.5.1 Mathematical Modeling for Surface Roughness

Equation (6) explained the mathematical relation correlating between turning process, cutting process conditions and the surface roughness value. The results of the computing software for this equation is shown as in table 5.

$$\begin{aligned}\textbf{Surface Roughness} = &+ 2.29587 - 0.016361*(\text{cutting speed}) + 5.94470 * (\text{feed rate}) - 1.75990 * (\text{depth of cut}) \\ &-0.034286 * (\text{cutting speed} * \text{feed rate}) + (4.76190E\text{-}004) \\ &* (\text{cutting speed} * \text{depth of cut}) +1.66667 * (\text{feed rate} * \text{depth of cut}) \\ &+ (5.75411E\text{-}005)*(\text{cutting speed})^2 - 1.61095 * (\text{feed rate})^2 \\ &+ 2.80631 * (\text{depth of cut})^2 \qquad (6)\end{aligned}$$

2.5.2 Mathematical Modeling for Roundness

The roundness affected with change in cutting parameters. It has been evaluated by computing the values of the different constants based on equation (7), using the designed expert computer software and the results of that equation is shown in table 5.

$$\begin{aligned}\textbf{Roundness} = &+ 4.12174 - 0.045474 * (\text{cutting speed}) + 4.62907*(\text{feed rate}) \\ &+ 0.47070* (\text{depth of cut})+ 0.015238* (\text{cutting speed} * \text{feed rate}) \\ &+ (9.76190E\text{-}003) * (\text{cutting speed} * \text{depth of cut}) \\ &- 6.55556* (\text{feed rate} * \text{Depth of cut}) + (9.62224E\text{-}005) * (\text{cutting speed})^2 \\ &- 0.72950* (\text{feed rate})^2+ 0.19011* (\text{depth of cut})^2 \qquad (7)\end{aligned}$$

2.5.3 Mathematical Modeling for Material Removal Rate (MRR)

Based on equation (8), the change in MRR related to change in cutting parameters' values can be evaluated. The results of the computer written software is revealed in table 5.

$$\begin{aligned}\textbf{Material Removal Rate} = &+10.695 - 0.093 * (\text{cutting speed}) - 69.0 * (\text{feed rate}) \\ &- 17.825 * (\text{depth of cut}) + 0.6 * (\text{cutting speed} * \text{feed rate}) \\ &+0.155 * (\text{cutting speed} * \text{depth of cut})+ 115.0 * (\text{feed rate} * \text{depth of cut}) \\ &+0.00001 * (\text{cutting speed})^2+ 0.0000001* (\text{feed rate})^2 \\ &+ 0.0000001* (\text{depth of cut})^2 \qquad (8)\end{aligned}$$

Table 5: Central Composite Rotatable Design, Different Controlling Parameters and Results

Ex. no.	Cutting Speed (m/min)	Feed Rate (mm/rev)	Depth of Cut (mm)	Surface Roughness (Ra) µm	Roundness (O) µm	Material Removal Rate (MRR) m^3/min
1	56	0.16	0.60	2.68	3.01	1.28723
2	80	0.08	0.90	2.25	2.38	1.512
3	115	0.03	0.60	1.42	1.29	0.545559
4	115	0.16	0.60	1.37	1.51	2.9295
5	174	0.16	0.60	1.04	1.09	4.57177
6	115	0.16	1.10	3.24	2.3	5.39291
7	80	0.23	0.30	1.66	2.35	1.449
8	115	0.16	0.10	1.51	1.23	0.466094
9	80	0.23	0.90	2.97	1.92	4.347
10	150	0.23	0.30	1.19	0.92	2.898
11	150	0.23	0.90	2.51	1.51	8.694
12	80	0.08	0.30	1.1	1.61	0.504
13	115	0.16	0.60	1.56	1.45	2.9295
14	115	0.16	0.60	1.9	1.48	2.9295
15	115	0.28	0.60	1.85	2.12	5.31344
16	115	0.16	0.60	1.26	1.41	2.9295

2.6 Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) provides a statistical test of the means for several equal groups. Ch. Maheswara *et al*., 2010. It is useful for comparing (testing) three or more means (groups or variables) for statistical significance. The efficiency of the three models stated in the previous section are tested through (ANOVA). Analysis results appear at tables 6–8. Variance can be defined as the mean of squared deviations around mean, or sum of squared deviations around mean value divided to freedom degrees. Testing efficiency of a model is usually done by computing F-ratio, lack of fit to pure error and comparing with standard value. If standard values exceed the value of the F-ratio, then the proposed model is adequate. As it is clear from the results of analysis, the lack of fit F-value is not significant, which proves mathematical models' adequacy and demonstrate effects of different machining conditions on surface roughness, roundness and rate of material removal. The most effective factor on surface roughness is the cutting depth followed by speed of cut, as in table 6.

Table 6: ANOVA for Surface Roughness Model

Surface roughness						
source	**Sum of squares**	**df**	**Mean square**	**F Value**	**p-value prob>F**	
Model	7.175	9	0.7973	8.9717	0.0010	Significant
A-cutting Speed	1.113	1	1.1127	12.521	0.0054	
B-Feed	0.481	1	0.4811	5.4135	0.0423	
C-Depth of cut	4.535	1	4.5347	51.029	< 0.0001	
AB	0.065	1	0.0648	0.7292	0.4131	
AC	0.0002	1	0.0002	0.0023	0.9631	
BC	0.011	1	0.0113	0.1266	0.7294	
A^2	0.072	1	0.0716	0.8058	0.3905	
B^2	0.001	1	0.0012	0.0133	0.9104	
C^2	0.919	1	09193	10.345	0.0092	
Residual	0.889	10	0.0889			
Lack of fit	0.517	5	0.1035	1.3943	0.3621	Not significant
Pure Error	0.371	5	0.0742			
Cor Total	8.064	19				

In table 7, speed of cut is the most influential factor in roundness error followed by cutting depth.

Table 7: ANOVA for Roundness Model

Roundness Model						
Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	5.4785	9	0.6087	8.5085	0.0012	significant
A-Cutting Spe	3.8266	1	3.8266	53.487	< 0.0001	
B-Feed	0.3793	1	0.3793	5.3014	0.0441	
C-Depth of Cu	0.7972	1	0.7972	11.143	0.0075	
AB	0.0128	1	0.0128	0.1789	0.6813	
AC	0.0841	1	0.0841	1.1748	0.3039	
BC	0.1741	1	0.1741	2.4328	0.1499	
A^2	0.2002	1	0.2002	2.7988	0.1253	
B^2	0.0002	1	0.0002	0.0034	0.9547	
C^2	0.0042	1	0.0042	0.059	0.8130	
Residual	0.7154	10	0.0715			
Lack of Fit	0.5955	5	0.1191	4.9676	0.0516	not significant
Pure Error	0.1199	5	0.0240			
Cor Total	6.1939	19				

In table 8, appeared the good effective way of cutting speed followed by cutting depth.

Table 8: ANOVA for Material Removal Rate Model

Roundness Model						
Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	5.4785	9	0.6087	8.5085	0.0012	significant
A-Cutting Spe	3.8266	1	3.8266	53.487	< 0.0001	
B-Feed	0.3793	1	0.3793	5.3014	0.0441	
C-Depth of Cu	0.7972	1	0.7972	11.143	0.0075	
AB	0.0128	1	0.0128	0.1789	0.6813	
AC	0.0841	1	0.0841	1.1748	0.3039	
BC	0.1741	1	0.1741	2.4328	0.1499	
A^2	0.2002	1	0.2002	2.7988	0.1253	
B^2	0.0002	1	0.0002	0.0034	0.9547	
C^2	0.0042	1	0.0042	0.059	0.8130	
Residual	0.7154	10	0.0715			
Lack of Fit	0.5955	5	0.1191	4.9676	0.0516	not significant
Pure Error	0.1199	5	0.0240			
Cor Total	6.1939	19				

2.7 Model Graphs

2.7.1 Turning Parametric Influence on Surface Roughness

Relationship among cutting speed, feed rate and surface roughness at constant value of cutting depth 0.6 mm, as in figure 2. Can see increasing of surface roughness with increasing feed rate and decreasing cutting speed. This is attributed to the increases in cutting forces and thus resulting in the reduction of the stability of the cutting operation and decrease in the quality of surface finish.

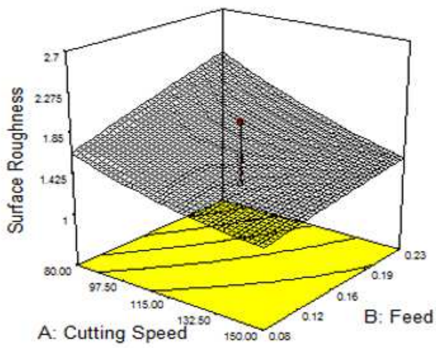

Figure 2: Change in Surface Roughness with Changing in Cutting Speed and Feed Rate.

Figure 3 reveals the relationship between surface roughness, depth and speed of cut at feed rate 0.16 mm constant value. It can be noted from the figure that the surface roughness increases on decreasing speed of cut due to increasing cutting force. Also, the roughness of the surface increases upon increasing the cutting depth, which is attributed to widening of the area of contact between the tip and the workpiece and thus changing the resulting force per unit length, which leads to chips' distortion while being removed.

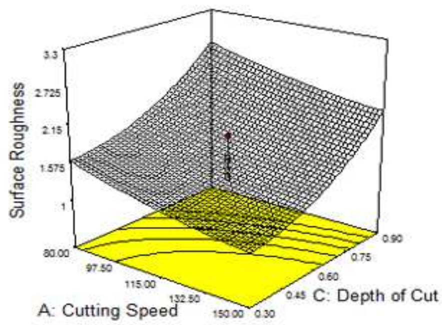

Figure 3: Influence of Speed of Cut and Cutting Depth on Surface Roughness

2.7.2 Turning Parametric Influence on Roundness

Figure 4 reveals the relation between roundness error, cutting speed and feed at 0.6-mm cutting depth constant value. Roundness error increases on decreasing the speed of cut and increasing the rate of feed, as in the figure. This is because decreasing the speed of cut and/or increasing feed rate, increase the force of cut for multivariate work-chuck-spindle system stiffness, which in turn affects the dimensional quality of the workpiece, as stated by M. Rahman and V. Naranayan, 1986.

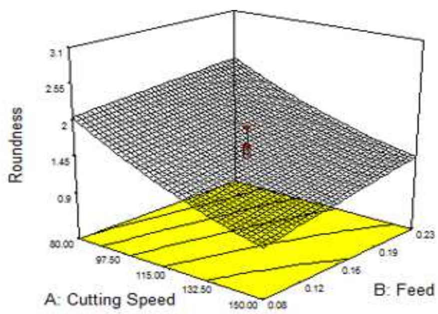

Figure 4: Influence of Speed of Cut and Feed Rate on Roundness

Figure 5 reveals the relationship between roundness error, speed of cut and depth of cut at constant value of feed rate of 0.16 mm. It can be noted from the figure that roundness error increases on decreasing the speed of cut and/or increasing cutting depth. Increasing the speed of cut is related to the increase in the cutting forces.

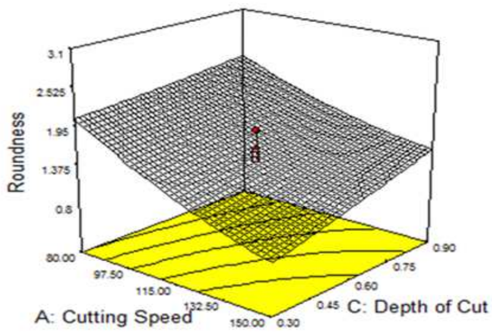

Figure 5: Relation between Speed of Cut, Cutting Depth and Roundness.

2.7.3 Turning Parametric Influence on Material Removal Rate

As it is clear from figure 6, increasing the speed of cut, feed rate and cutting depth increase the rate of material removal, as it follows the relation.

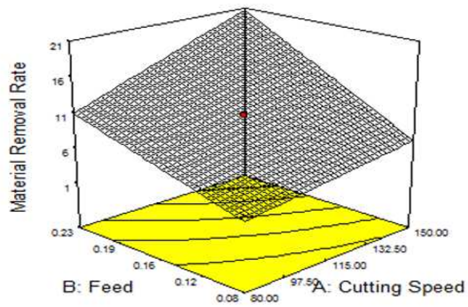

Figure 6: Relation between Speed of Cut, Feed Rate, Cutting Depth and Rate of Material Removal.

3. DUELIST ALGORITHM

Duelist Algorithm (DA) is a new evolutionary optimization algorithm proposed by Biyanto *et al.* [20] inspired by human fighting competitions. They showed that the DA is based on GA, but it is more efficient when compared to genetic, particle swarm optimization and imperialist competitive algorithms. DA contains a certain population of duelists in which each duelist would fight another one to determine the winner and loser, depending on each duelist's capability of fighting. Fighting capabilities are defined using objective function. This determination is for choosing the improvement that should be provided to them. Fighting capabilities consists of binaries with a specific length called skill set, resulting in new fighting capabilities. On the other hand, the loser will learn from the winner how to fight better. This training creates a new duelist from a lesser one with some new skill sets copied from the winner that beats them. Champions, which are the ones with the best fighting capabilities, are selected to maintain the best solution for each iteration. Champions would train new duelists as same as they are, which will add some more duelists to the tournament. To maintain the duelist's registered number fixed in the tournament, the worst fighting duelist's capabilities are eliminated. This process is repeated until stopping criteria is satisfied.

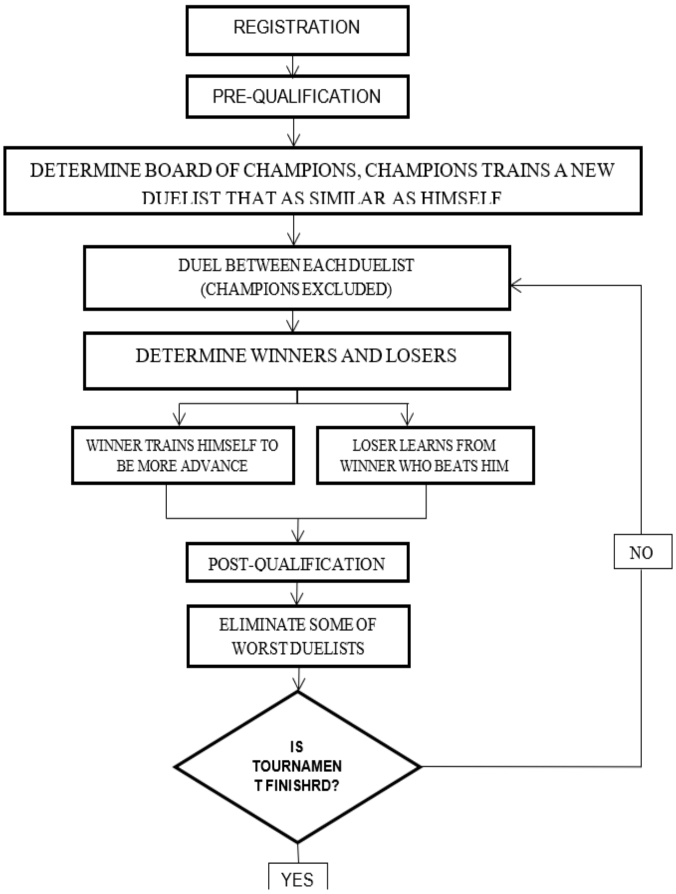

Figure7: Duelist Algorithm DA Flowchart.

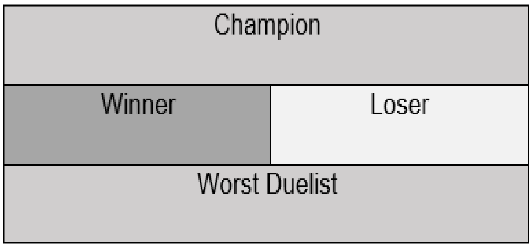

Figure 8: Duelist's Classification.

3.1 Steps of Duelist Algorithm

As revealed in figures 7 and 8, the flowchart of DA explains its sequences as follows:

3.1.1 Duelist Registration

This is the first step of the algorithm in which each duelist is registered in a binary array called skillset.

3.1.2 Prequalification Test

Each duelist undergoes a prequalification test for evaluating its fighting capabilities depending on its skillset.

3.1.3 Determination of Champions

Keeping the best duelist competing depending on champion determination. Champion trains new individual for being well. Replacement champion in the competition and joining the next stage is done through a trained duelist.

3.2 Defining Each Duel Schedule

Each duelist schedule is set randomly. Every competitor competed related to its capability of fighting and luck. The winners and losers are determined for each match. The duel uses simply logic. If competitor (A) has capability of fighting plus its luck greater than the competitor (B), then A will be winner and vice versa. Random function is used to determine the luck to avoid local optimum.

3.3 Case Study

In our work, the case study which the DA applied for turning process conditions, optimization is related to the models developed in section 4. For demonstration and validation duelist algorithm, an example is considered for objective function, which is used to minimize surface roughness and roundness, given by equations 6 and 7, respectively along with maximizing the material removal rate, given by equation 8.

3.4 Parameters Bound

The three turning parameters (conditions) are considered in that the presented works are feeding rate, cutting depth and speed of cut. The upper - lower bounds of these conditions are given below:

$80 \le$ cutting speed ≤ 150

$0.08 \le$ feed rate ≤ 0.23

$0.3 \le$ depth of cut ≤ 0.9

The various steps of the duelist algorithm are now applied as follows:

Step 1: Defining the number of duelists in the competition as well as the fighting capabilities. In our problem, the number of population is 100, which describes the number of duelists in the tournament and fighting capabilities as 50, then the duelists are registered in the game; the registration is a binary array called skillset.

Step 2: Evaluating the competitors by setting a prequalification in terms of their fighting capabilities.

Step 3: The game starts between different duelists to classify the players into champions, winners and losers. The champions train new duelists to replace them in matches. The fitness function is specified as follows:

Fitness Function = Material Removal Rate Model – Surface Roughness Model – Roundness Model.

The negative sign is to indicate that both the Surface Roughness and Roundness Models shall be minimized, while Material Removal Rate Model is to be maximized.

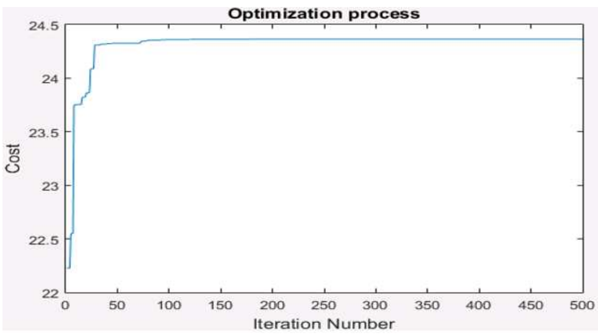

Figure 9: Convergence of Duelist Algorithm.

Step 4: The game starts and the players compete, the match ends with winners and losers, and losers train from winners, who beat them and the winners develop qualifications. Worst duelists are eliminated to keep the number of populations fixed, and the process continues till the best solution is reached and maintained without change through the specified number of iterations. The game is the fitness function, while the players are the different values of process conditions that compete for getting the best possible values for the fitness function. Figure 9 explains convergence of duelist algorithm. The algorithm requires 75 to 100 iterations to reach the optimum value and table 9 reveals the corresponding optimum values.

Table 9: The Optimum Values of Process Parameters and the Corresponding Output

Process Parameters	Optimum values	Surface Roughness	Roundness	Material Removal Rate
Cutting Speed (m/min)	149	2.1198	1.5120	27.9975
Feed Rate (mm/rev)	0.23			
Depth of Cut (mm)	0.84			
Confirmation Test		2.14	1.58	28.8
Error %		0.95	4.5	2.87

4. CONCLUSIONS

The study presents modeling and optimizing of turning process conditions during dry turning process of AISI 4145 alloy steel using cemented carbide tool. The main objective considered is minimization of surface roughness and roundness error along with maximizing the material removal rate applying a novel technique known as duelist algorithm. A mathematical model depending on Response Surface Methodology (RSM) approach is developed to correlate between the speed of cut effects, rate of feeding and cutting depth of various machining process performance conditions, as roughness of the surface, roundness error and rate of removal material. Optimum values of the process conditions are then obtained due to developing Duelist optimization algorithm. The rate of convergence and solution accuracy are used as performance measures for the Duelist algorithm. Analysis of the resulting data appeared:

- Duelist algorithm possesses convergence rate of about 75 iterations to converge to optimal solution.
- Based on the limits employed in the experimental process, the maximum error was 4.5% between the validation data and the predicted data.
- The optimum turning conditions to obtain the minimum roughness of the surface and roundness values errors alongside maximum material removal rate values within proposed ranges.
- The Duelist algorithm is robust, simple in application and an effective optimization algorithm, which is used effectively in the optimization of multi-objective problems.
- The algorithm is employed to find the process conditions' optimal values for other machining processes.
- Duelist algorithm can be used in online optimization because of its convergence rate.
- Applying the Duelist algorithm can reduce the cost and time of operation by obtaining the optimum solution.

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